State-of-the-Art fNIRS for Clinical Scenarios: A Brief Review

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Abstract. Technologies that monitor human health, diagnose health problems, or contribute to the study of brain functions and translate them into commands in the pursuit of finding replacements for those who have lost limbs to improve their lives are techniques worth studying. Today, the Neuroimaging technique functional near-infrared spectroscopy (fNIRS) has become one of the pioneering technologies in various applications, especially in the medical field, and this technology has gone through major events and attracted the attention of researchers for numerous and diverse studies. Considering recent indications for this method, a brief review highlights the state-of-the-art of this method and offers various recent uses of its directions toward clinical application scenarios, in particular in the field of artificial limbs and neurological rehabilitation. In addition, this review provides insight into the expected uses of this method shortly. The research methodology included the theory of fNIRS, its basic principles, systems, and its relationship with other neuroimaging methods considering contemporary scientific modernity. Among hundreds of scientific publications, the selection of popular and fruitful research and articles related to the subject of review and their analysis led to beneficial results. Monitoring, diagnosing, and finding solutions to physical problems may fall a great deal on the responsibility of this technique, which is still in the circle of modern scientific research that has yielded discoveries even at the expense of the challenges it faces by combining it with another technology to fill its inherent flaw, which means encouraging the expansion of future studies of this technology, which may be the most promising technology for several clinical applications shortly.

Keywords: Functional near-infrared spectroscopy (fNIRS) · Functional magnetic resonance imaging (fMRI) · Hemodynamic response · Electroencephalography (EEG) · Electromyography (EMG) · Brain–computer interface (BCI)

1 Introduction

Science has not cast its shadows on one field without another, or on one technology without another. Science is characterized by its comprehensiveness, which is based on ideas drawn by the need for something. The wheel of science will never back; it is always moving forward. However, if we look back at the scientific discoveries recorded

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300 years ago, we find them to be simple compared to the current discoveries. Replacing one technology with another, or updating the same technology, are stations to which science has had its touch.

The health problems of humans, in fact, never stop, and the grinding wars leave behind many physical handicaps, this necessitates the pursuit of the development of any treatment or technology that would restore human health to exercise his role in this life. The neuroimaging technique functional near-infrared spectroscopy (fNIRS) is one of the emerging technologies pursuing this purpose. Modern neurointerfaces have a functional role based on the real-time detection of characteristic waveforms (patterns) of brain activity using neuroimaging methods, such as fNIRS [1], and on the transformation of the information obtained into control commands for devices (for example, exoskeleton, bioprosthesis, wheelchair, neurointerfaces of attention control, etc.)

Historically, five decades and more than half of the sixth, namely in 1977 Jöbsis used the technique for the first time to noninvasively assess changes in human brain oxygenation due to hyperventilation [2]. In the terminology of the intersection of sciences, the fNIRS technique falls within the concept of interdisciplinarity, which is consistent with the concept of brain-computer interfaces (BCI) in scientific literature. The scientific research involved in this technology is extensive and varied in different fields such as physics, biology, neuroscience, psychology, and others, but artificial intelligence is a common factor that accompanies the work of this technology. fNIRS, like other neuroimaging techniques, has advantages and disadvantages.

There are challenges facing this technique because of its relatively modern origin. These challenges are still within the framework of the study, as there are recent studies that are working to reconsider these challenges, such as rethinking delayed hemodynamic responses [3]. The main changes in the fNIRS signal (i.e., oxygenated HbO_2 and deoxygenated Hb changes) occur in two compartments: (i) the cerebral compartment, where the signal changes within the cerebral compartment and includes three main components: neuronal evoked changes, systemic evoked changes, and vascular evoked changes, and (ii) the extra cerebral compartment, where the signal changes in the extra cerebral compartment and includes three main components: systemic evoked changes, vascular evoked changes, and muscular evoked changes. Systemic physiological changes also affect BOLD-fNIRS signals measured at the head. These changes have been demonstrated by several studies [4], changes at the expense of sex [5], because systemic physiology contains components originating from neurovascular coupling and systemic physiological sources. This indicates the need to monitor these changes to increase the complete understanding and correct interpretation of signals. fNIRS is a new emerging technology that uses different methodologies for different studies. Regarding the question of how systemic physiological signals are processed and analyzed within fNIRS methodologies, several challenging signal characteristics such as non-instantaneous and non-stationary coupling have not been addressed, and additional ancillary signals have not been optimally exploited. Some methodologies may be unable to analyze fNIRS systemic physiological data or may have just begun [5]. For example, the approach of combining temporally embedded canonical correlation analysis with a general linear model that allows flexible integration of any number of modalities and ancillary signals generally improves the detection of task- or stimulus-evoked hemodynamic responses in the presence of systemic, low-variability physiological confounders, such as the fNIRS signal-to-noise ratio, and some stimuli or trials [6].

The main essence that distinguishes fNIRS is what makes it complementary to the other system or takes advantage of the other system to compensate for its inherent deficiency to form an integrated system [7]. This essence can be achieved by mixing with other technologies, such as electroencephalography (EEG) [8], which is characterized by its very high sensitivity to artifacts and noise, unlike fNIRS, as the latter is less susceptible than EEG [9]. In the field of prosthetic control, electromyography (EMG) cannot create a prosthetic system in those whose residual muscles in their limbs are unable to enhance signals of electrical activity, but this problem is solved with fNIRS. Due to the limited ability of fNIRS to penetrate the skull to a depth of less than 3 cm, functional magnetic resonance imaging (fMRI) can help identify the active areas of the scalp that innovate the fNIRS technique in recording brain signals at the active area, according to the BCI concept. On this basis, this review examines the state-of-the-art fNIRS technology, whether in its independent use or combination with other technologies within various stations for clinical applications.

2 Research Methodology

Even though fNIRS is used in various studies and has wide application in various fields, the researcher's methodology was limited by 99% to recent research, articles, and studies from 2020 to 2023 with a trend toward clinical scenarios. The ultimate purpose of this review is to examine the extent of the neuroimaging technique fNIRS and its relationship to other technologies. In addition, amid the challenges, this review linked the compensatory solutions documented in the scientific literature to these challenges, based on known databases, namely, Scopus, Google Scholar, and various sites, such as the first site https://scholar.google.com/ and others. In addition, various links are indicated as https://www.mdpi.com/journal/sensors, https://www.refseek.com and others. Finally, hundreds of relevant articles were reviewed, many of those that do not go to the core of the topic were neglected and those that do not carry modern ideas were deleted and limited to 60 scientific articles as authoritative articles that keep pace with scientific modernity, after which followed the recommendations of experienced people and considered their comments to strengthen the methodology and targeted analysis.

3 Basic Principles of fNIRS and Hemodynamic Response

The principle of near-infrared spectroscopy (NIRS) was first obviously defined by Jobsis, who reported that the relatively high degree of brain tissue transparency in the NIR range enables real-time non-invasive detection of hemoglobin (Hb) oxygenation using transillumination spectroscopy, i.e., the possibility of detecting changes in adult cortical oxygenation during hyperventilation by NIRS [2]. The principle of operation of most modern neural interfaces is based on mapping the brain and identifying areas of its activity. fNIRS is the most modern non-invasive neuro interface based on the analysis of the chemical activity of the nervous system based on the blood oxygenation level-dependent principle. The BOLD principle is based on the detection of the concentration of hemoglobin (HbO2 and Hb) in certain areas of the brain. The main challenge with fNIRS is the limited depth sensitivity that is based on the principle that the emitted photons will only interrogate the cortical surface, which will have a shorter time of flight compared to the delayed photons that it has, which can reduce its ability to detect brain activity and make the acquired signal vulnerable to contamination from the tissue outside the brain and therefore vulnerable to information loss or little information being revealed. The two main phenomena affecting light propagation in tissue are scattering and absorption. Scattering refers to a change in the direction of a photon. The main scattering constituents of NIR light include lipoprotein membranes, red blood cells, mitochondria, and other cellular components. Absorption is the energy transfer from a photon to atoms or molecules in the tissue. The main chromophores that absorb light in tissue are Hb, HbO2, H2O, and lipids.

fNIRS in terms of wavelengths to extract information about the concentration of the chromophore at a wavelength below 650 nm, most of the incident light will be absorbed by hemoglobin; above 950 nm, the light will be absorbed by water, while at wavelengths from 650 to 950 nm window, the absorption of light by tissues is relatively low; in other words, low signal-to-noise ratio, which is called the optical window, is widely used with fNIRS method (see Fig. 1). In this regard, scientific studies have found that the optimal wavelength is approximately 830 nm, which means that the optical visual response is represented by changes in the concentrations of oxyhemoglobin and deoxyhemoglobin during brain activation [10].

In terms of distance, the typical distance from the source to the detector is approximately 3 cm (see Fig. 2). The depth penetration of light is associated with this distance. When the distance between the source and detector was small, the local detection of brain activity increased, which significantly enhanced the spatial resolution. For this purpose, detectors that use a time window approach for early separation from late photons have been developed [11].

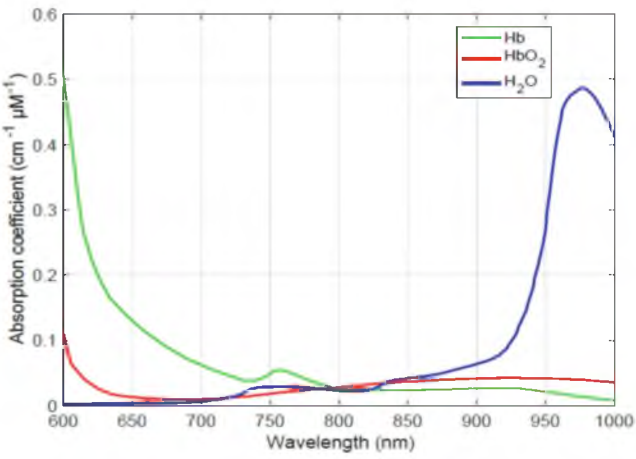

Fig. 1. Absorption spectra of the chromophores Hb, HbO_2, and H_2O

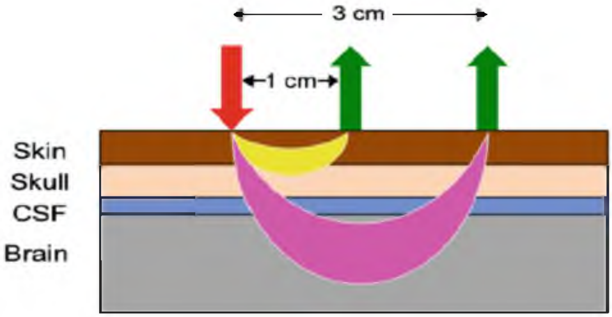

Fig. 2. Shows the path of a photon in the form of a banana, whereas the yellow color indicates the path of the photon in the tissue between the source and detector at a distance of 1 cm and b. Pink is the path of the photon in the tissue between the source and detector at a distance of 3 cm [12].

The hemodynamic response (i.e., increased HbO_2 and decreased Hb) results from regional increases in blood flow and blood volume that exceed the corresponding increase in regional metabolic demand. These changes in the concentrations of HbO_2 and Hb can be determined by measuring the absorption changes at two or more wavelengths of light. A disadvantage that overshadows the fNIRS method is the delayed hemodynamic response (3–5 s). Artificial networks designed to classify and optimize fNIRS signals do not consider this inherent drawback, which causes many optimization and application problems. Seeking alternatives that differ in structural composition and give a better result is the focus of this study. fNIRSNet outperforms other deep neural networks on open-access datasets. In particular, when fNIRSNet contains 498 parameters, it is 6.58% higher than that of a convolutional neural network (CNN) with millions of parameters on mental arithmetic tasks, and the floating-point operations of fNIRSNet are much lower than those of CNN. Therefore, fNIRSNet is compatible with practical practices and reduces the hardware cost of BCI systems [3].

For more information, please visit https://github.com/wzhlearning/fNIRSNet. The work of the fNIRS method at the time of its discovery was not similar to its current work. fNIRS as a completed system (hardware /software) is closely related to physics. This work fits and is completely based on the concept of neural interfaces, where the artificial intelligence revolution is at its apogee.

Understanding brain functions is essential for efficient BCI applications. The classification of brain states can be performed in real-time by the registered brain activity caused either by spontaneous physiological processes or by external stimulation using an intelligent BCI system.

BCIs are usually divided into two folds: the first, unidirectional, which is receiving signals from the brain or sending them to it, and the second, bidirectional, which is allowing information to be exchanged in both directions, and this depends on the direction of their work [13]. According to the principle of operation, the BCI can be classified as shown in Fig. 3 [14, 15].

In terms of hybrid systems, BCI is not limited to single data processing but extends to double or triple data processing [16]. For example, hybrid BCI of active and passive

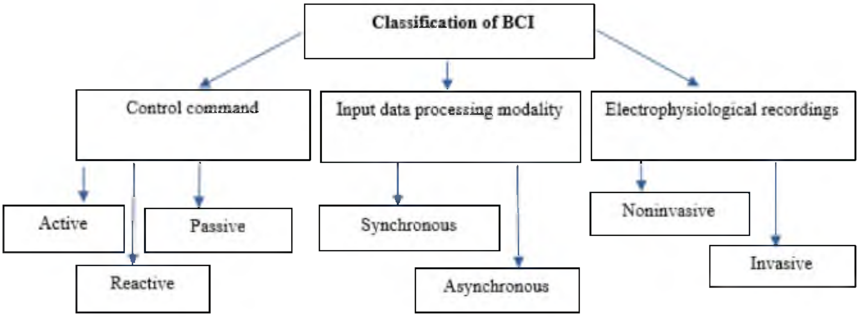

Fig. 3. Classification of BCI.

are more effective, enable estimation of the operator's mental state, and take advantage of independent techniques such as fNIRS and EEG or hybrid technologies such as EEG-EMG [17]. The principle of operation of the BCI is indicated in Fig. 4 and includes three main and sequential steps: (i) signal acquisition, (ii) signal processing, and (iii) application interface.

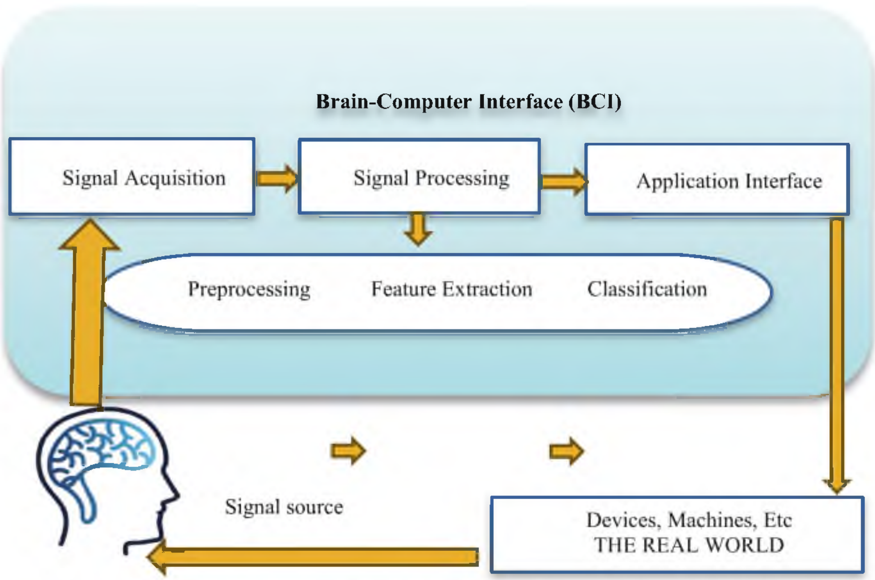

Fig. 4. Principle of operation of the BCI in three main sequential steps

4 fNIRSAS: A Hardware – Software System

Understanding proper analysis techniques is critical to ongoing success in fNIRS research. To not exceed the scope of this review, we limit ourselves to referring to the recently used models and analytical methods. fNIRS-BCI as (hardware-software) system is classified based on functionality.

In terms of hardware, when comparing fNIRS with other medical technologies, it falls into the category of equipment destined for miniaturization. According to fNIRS research in the scientific and practical fields, there are three main types of fNIRS instrumentation: continuous wave, frequency-domain, and time domain. There may be proposed approaches based on these types such as the high-density fNIRS-BCI approach, where the utility of spatial-temporal-CNN for high-density fNIRS-BCI was investigated. Several fNIRS devices such as NIRx NIRSPORT systems) that allows the subject to be fully ambulatory and move freely during recording [18]. Shortly, as has been already done with EEG [19], fNIRS BCI may be integrated with virtual reality headsets to enhance user experience through neurofeedback, or to gather real-time data on users' mental states to be used, this proves the accentuation of this technique with other preferential advantages.

In terms of software, in remark of Fig. 4, the optical evoked (fNIRS principle) of the signal source, in turn, will lead to brain signal acquisition resulting from this excitation. This signal is not without impurities, noise, artifacts, etc. Therefore, the role of the signal processing (signal analysis) stage, includes the stages of pre-processing, feature extraction, and classification that precede the actual application stages. The main noise sources are instrumental noise, experimental noise, and physiological artifacts. Methods for removing artifacts from the fNIRS signal are based on various methods of signal decomposition and transformation, and these methods have a fairly high accuracy in the selection of artifacts, such as principal component analysis, wavelet transforms, and filter-based feature reduction techniques and others [20–22]. Although these methods exist, there are new approaches to the decontamination of data using the cumulative curve fitting approximation algorithm for filtering signals to reduce the distortion effects due to the instability of data [23].

The noise removal of the fNIRS signal depends on the different types of filters used and there are perfect filters, but they are optimal [24] for a task and are not ideal for all tasks performed by fNIRS. Therefore, it is necessary to choose different filtering methods and set different filtering parameters to obtain good results. fNIRS has typical time series properties that make the signal processing stage uncomplicated. Modeling and forecasting the behavior of chaotic systems are tasks of artificial intelligence; therefore, neural networks play an important role in the classification of input data and are very suitable for studying and predicting signals of non-stationary brain activity. Data pre-processing may vary before reaching the classification stage, and the pre-processing stage can be omitted because of the deep learning method without degradation of classification performance. With 91% accuracy, the residual neural network model can classify patterns of motor activity in addition to target commands [1]. To generate control commands for a prosthetic arm using fNIRS for three degrees of freedom, out of ten, eight correct movements were predicted in real-time by classifiers artificial neural network and linear discriminant analysis [25, 26]. According to average accuracies, there may be a difference in classification techniques based on machine learning, such as classifiers support vector machine (SVM), k-nearest neighbor, linear discriminant analysis (LDA) from those based on deep learning, such as classifiers CNN, long short-term memory (LSTM), and bidirectional long short-term memory and there may be a superiority of classifiers over each other [27].

Neural networks based on the deep learning method have natural noise suppression capabilities and therefore, introducing as much information as possible into known classification algorithms will improve the accuracy of classification [28]. The signal processing stage is illustrated according to the simplified Fig. 5.

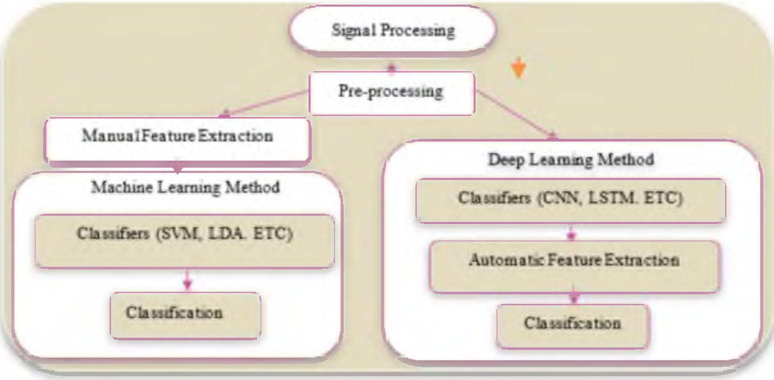

Fig. 5. The steps of the signal processing stage.

5 fNIRs Challenges and Solutions

Despite its clear advantages that make it environmentally valid for applications to various populations, including sick and even healthy children and elderly adults, its disadvantages still present significant challenges. As is known, the fNIRS technique has limited penetration, it is reduced to recording the signals of the cerebral cortex and in turn, the fMRI technique has the miraculous ability to penetrate, and this may help a lot in identifying the active areas by fMRI, which reduces the disadvantage of fNIRS technique in other words, addresses the challenge of poor penetration in fNIRS technique.

In experimental studies, the typical distance between the source and the detector is 3 cm, and the depth of penetration of the banana-shaped light into the tissue is closely related to this distance (as shown in Fig. 2 [12, 29]. This means that when identifying active areas, the distance between the source and the detector can change, and the penetration depth increases. From another point of view, when fNIRS is used in combination with another technique, a multimodal data integration system at the sensor level must overcome the challenges of non-instantaneous and non-linear coupling dynamics between modes, different temporal and spatial resolutions, unimodal outliers, and possibly others [3].

The required high temporal and spatial resolution that fNIRS lacks can be compensated by the magnetoencephalography technique, which also addresses this challenge [7]. The linear theory of the hemodynamic response function support low-frequency (<0.2 Hz) analysis while that analysis of the nonlinear high-frequency effects (0.2–0.6 Hz) seen in fNIRS makes it possible to comprehensively analyze cortical neurovascular activity and this leads to further reconsideration of the dynamics of the linear and nonlinear hemodynamic response in other words, at slow and fast frequencies [30]. The challenges of biological dynamics, there are attempts to rethink the delay in the hemodynamic response, which is a disadvantage of this technique, recent studies have relatively proven that the delay in the hemodynamic response was not as it was thought [3].

These are clear evidence that there are relentless attempts to delve into the challenges of fNIRS technology, which contributes to bringing this technology to the interface of ideal technologies, whether individually or using a technical combination.

6 fNIRS with Other Neuroimaging Methods

The ease of setup and portability make fNIRS a very suitable technique along with other techniques. There are many recent scientific studies that combine this technique with other techniques, for example, with fMRI to evaluate hemodynamic responses in motor tasks (determining the active area) [29], and what fNIRS lacks, magnetoencephalography (MEG) can provide high temporal and spatial resolution when combining these two techniques [7], but nowadays it is most commonly used with EEG and EMG in particular, in directions freedom to control prosthetics.

6.1 With EEG

The combination of EEG-fNIRS carries a clear signal and is a promising approach because of its low cost, portability flexibility, low interference, and good spatial and temporal resolution [31]. In terms of signal recording, combining EEG and fNIRS provides additional information about the bioelectric activity of the brain. In addition, the combination of fNIRS and EEG has certain unique characteristics, as the rationale behind their combination is their dependence on a physiological phenomenon called neurovascular coupling [32] within the brain, which makes them more useful in certain applications. At present, there are numerous studies active in the study of the combination of these techniques, particularly for prosthetic control purposes. This greatly encourages the creation of a system that may be the most promising for controlling prosthetics [33].

6.2 With EMG

Surface electromyography measures the electrical signal generated by the skeletal muscles on the surface of the skin. The absence of muscle or the presence of muscular atrophy renders this technique completely inappropriate for creating a prosthetic system [34]. Recent studies have demonstrated positive correlations between EMG signals and fNIRS. These correlations may provide evidence that a combination of these two techniques can be used to further explore the mapping relationship between brain activity and motor task execution and could be directed toward clinical studies [35, 36].

7 fNIRS in Clinical Applications

As a safe, noninvasive, relatively low-cost, radiation-free, and easy-to-install technology, its entry into the field of applications that care about human health is very convenient. In the field of application of fNIRS toward clinical scenarios, the wavelength parameters are not completely uniform, which means that a device can be developed for each wavelength within the optical window (650–900 nm). At the best wavelengths (730, 808, and 850) three devices have been developed that provide accurate changes in the concentration of oxygen in the blood [37]. With the development of Chinese medicine, patients receiving acupuncture and moxibustion interventions was based on the application of fNIRS.

fNIRS may pioneer some applications that are the focus of recent studies, and which may confirm its quality, for example controlling robotic devices, including exoskeletons, to augment human capabilities; detection of brain diseases, assessment and monitoring of psychophysiological conditions and rehabilitation of people after brain damage, for example, restoration of motor skills after stroke. in addition, in Table 1 some of the results of experimental studies and the task of fNIRS in its independent use or combination (towards clinical applications) [14, 38].

Table 1. Experimental studies for the years (2020–2023) and the role of the fNIRS method.

Ref	No. of Participants	Task of fNIRS	Results
[12]	15 healthy subjects	Detection of brain activity in patients with disorders of consciousness	Absence of any training effect and absence of mental fatigue
[39]	15 healthy and 3 transhumeral amputee subjects for 6 arm motions	With sEMG to improve classification accuracy, thus improving the control performance of multifunctional upper-limb prostheses	The study helps to achieve the control of electro-muscular multifunctional prostheses for amputees
[28]	22 subjects	Classification of the Imagery Task	Deep learning methods outperform classical methods and achieve a classification accuracy of 97%
[40]	20 subjects	With EEG, investigation of the relationship between hemodynamic response and oscillatory activity in the brain	Significant improvement in the accuracy of ankle joint classification 93.01 ± 5.60%

(*continued*)

Table 1. (*continued*)

Ref	No. of Participants	Task of fNIRS	Results
[41]	29 healthy subjects	With EEG, the evaluation of motor imagery contributes to neurorehabilitation applications	By 5.39% increase the classification accuracy of the motor imagery task by comparing two algorithms, one traditional and one proposed

8 FNIRS for the Prospective Future

Experimental scientific studies have overcome many of the challenges facing this technology, as they have proven that the defects in the fNIRS technique are still the focus of study and may be removed or compensated for by the advantages of other technologies.

The insight created by recent scientific studies involving this technique opens the doors to future studies of interest in this method, both on an individual level and on a hybrid level with another technique to complement each other. Time-resolved-fNIRS can serve as a promising portable tool for detecting brain activity at the bedside and providing an objective marker for assessing consciousness in patients with disorders of consciousness [19]. What future studies are looking for is briefly described in Table 2.

In a study related to the topic of the article, the girl in the photo is a fifth-stage medical student named Shelly from India. She is experimenting to research and develop

Table 2. Experimental studies for the years (2020–2023) and the role of the fNIRS method.

Ref.	Method	Importance of Study	Future Vision of the Study
[5]	fNIRS	To study the embodied human brain	Opening new horizons for exploring the complex interplay between brain activity and body physiology
[42]	fNIRS + EEG	To evaluate cortical excitability and motor imagery (BCI)	A promising method for improving traditional motor training methods and clinical rehabilitation
[29]	fNIRS + fMRI	To assess hemodynamic response in motor tasks	The possibility of translating spatial neuronal activity information and the validity of measurements to uncover motor function
[43]	fNIRS	Offers a systematic assessment of fNIRS, encompassing the basic theory, experiment analysis, data analysis, and discussion	Strengthen safety standards and guide insightful recommendations for subsequent studies

Fig. 6. Shows a photo of one of the study participants, performing experimental tasks in the field of prosthetics in one of the laboratories of the Belgorod State National Research University, Russia.

a control system for prostheses, and the results of the experiment will be announced in the near future (see Fig. 6).

9 Conclusion

Until now, fNIRS is still in the circle of scientific research and in several areas of studies, e.g., fNIRS as a neural interface for creating a control system for prostheses. Scientific studies have proved that fNIRS forms a combined system with other technologies, superior to the autonomous one, when the results obtained from the hybrid system were compared with the results of the independent system. In mathematical logic, fNIRS is used as a common factor with other techniques.

A system that combines it with other technologies can obtain what is characteristic of those technologies or it awards what is characteristic to complement the lack of those other technologies. This is what makes it a pioneer in the growing studies of our time that use fNIRS together with other techniques under the term of hybrid systems. Nevertheless, combining fNIRS with noninvasive such as EEG, EMG, transcranial magnetic stimulation and others can reveal an immediate assessment after a motivational intervention provides timely feedback on the treatment effect. This means that there are solutions to some challenges facing this technology, and the solutions are documented by experiments and practical studies. Thus, monitoring, diagnosis, and development of a treatment plan are tasks that modern medical technologies enter immersion toward contribution and ideal correction clinical scenarios.

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